An effective face recognition method using guided image filter and convolutional neural network

Yallamandaiah S., Purnachand N.
School of Electronics Engineering, VIT-AP University, Amaravati, Andhra Pradesh, India

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ABSTRACT

In the area of computer vision, face recognition is a challenging task because of the pose, facial expression, and illumination variations. The performance of face recognition systems reduces in an unconstrained environment. In this work, a new face recognition approach is proposed using a guided image filter, and a convolutional neural network (CNN). The guided image filter is a smoothing operator and performs well near the edges. Initially, the Viola-Jones algorithm is used to detect the face region and then smoothened by a guided image filter. Later the proposed CNN is used to extract the features and recognize the faces. The experiments were performed on face databases like ORL, JAFFE, and YALE and attained a recognition rate of 98.33%, 99.53%, and 98.65% respectively. The experimental results show that the suggested face recognition method attains good results than some of the state-of-the-art techniques.

Corresponding Author:

Purnachand N.
School of Electronics Engineering
VIT-AP University
Amaravati, Andhra Pradesh 522237, India
Email: chanduinece@gmail.com

1. INTRODUCTION

The face is an important biological trait that differentiates an individual from others. Face recognition is a process of extracting features and identifying individuals, and it is an efficient approach among many biometrics because of its full automation and uniqueness [1]. Preprocessing, feature extraction, and classification are the three steps in the face recognition task. The extraction of features and the construction of the proper classifier play a major role in the face recognition process.

Face recognition has become popular because of its utility in different areas such as communication, file management, human-computer interaction, surveillance, security, and law enforcement. In particular, face recognition is widely used to identify missing babies, detect passport frauds, unlocking apps on mobile phones, and stop blacklisted persons in restaurants. The efficiency of the face recognition systems reduces because of variations in illuminations, poses, expressions of the person. In an uncontrolled environment, the face images are affected by different illuminations and noises. A guided image filter has a variety of applications such as noise reduction, haze removal, enhancement/smoothing [2]. Recently convolutional neural networks producing good results in the case of image classification. The tradeoff when moving from traditional approaches to deep learning approaches is training time i.e. initially it takes a long time for training the data to the CNN, but the classification accuracy will be high compared to earlier methods. To deal with the various illuminations, poses, and expressions of the person, this paper proposes a new face recognition method using a guided image filter and convolutional neural network (CNN).

The structure of the paper is planned as follows: Related work is discussed, in Section 2. In Section 3, the suggested face recognition method is explained. The experimental outcomes are demonstrated in Section 4. The conclusion of the paper is presented in Section 5.

2. RELATED WORK

Feature extraction and the construction of the classifier play a crucial role in the face recognition process. The principal component analysis (PCA) is a prominent method for feature extraction. Kirby and Sirovich used principal components to represent human faces [3]. Turk *et al.* utilized the plan of Ref. 3 for face detection and recognition [4]. PCA reduces the dimension and eliminates correlation, however, it is not appropriate for classification [5], [6]. Meedeniya and Ratnaveera proposed an enhanced face recognition method through the variation of PCA, in which the authors performed the economic size singular value decomposition to generate a unitary matrix [7].

Linear discriminant analysis (LDA) is an eminent dimensionality reduction method, but it fails when the count of training samples is less compared to the count of dimensions of the feature space [8]. To overcome this problem Belhumer *et al.* proposed the fisher faces method [9]. Yun and Ruan propounded enhanced fisher's linear discriminant (EFLD) method and it outperforms the earlier algorithms [10]. Zhou *et al.* suggested a face recognition method by combining a Non-Negative Matrix Factorization with a Radial Basis Function classifier [11]. Abusham *et al.* demonstrated an approach for face recognition by fusing Locally Linear Embedding and PCA [12]. Local binary patterns (LBP) [13] and local phase quantization (LPQ) [14], [15] have attained good face recognition implementation in constrained environments. The performance of these handcrafted features reduces considerably in an unconstrained environment. Zhou *et al.* introduced a face recognition method using PCA and LDA [16]. Dai *et al.* manifested a decorrelated 2D-feed-forward neural network (2D-FNN) ensemble with random weights [17]. The feature-level fusion of local binary patterns and coefficient enhancement algorithms on contourlet-subbands made a robust expression invariant face recognition system [18]. Khan *et al.* proposed a system that can recognize faces under varying expressions and illumination using particle swarm optimization (PSO) [19]. Tai *et al.* proposed the orthogonal procrustes problem (OOP) as a framework to pose changes in face images [20]. Li *et al.* introduced a projective low-rank description method for face recognition [21]. Chen Y *et al.* addressed the problem of multi-pose classification using 2D-Gabor features and the Deep Belief Nets [22]. Yin *et al.* suggested multi-task learning for recognizing faces with the pose and expression estimation as the side tasks [23]. Ding *et al.* introduced an improved human activity recognition system based on a random forest classifier [24]. Liao *et al.* suggested a novel cluster multiple kernel learning algorithm for recognizing the oil painters [25]. Muqeet *et al.* presented a face recognition method by utilizing directional wavelet transform and local binary patterns [26].

In recent years CNN methods have grabbed substantial attentiveness in face recognition. The CNNs considerably enhances the model generation ability by establishing effective regularization strategies such as dropout [27]. The research group at Facebook developed a deep learning facial recognition system named DeepFace [28]. Wu *et al.* discovered the correlations among the sustainable development goals and communication technologies [29]. Various pattern recognition algorithms for human activity recognition were reviewed and discussed in [30]. Lin *et al.* propounded a new robust dictionary learning approach for face recognition [31]. Georgel *et al.* used deep stacked de-noising and sparse auto-encoders (DSDSA) for face recognition [32]. In this work, a new face recognition technique is proposed using a guided image filter and a convolutional neural network.

3. PROPOSED WORK

This work proposes a new approach for face recognition using a guided image filter and a CNN. The proposed method consists of the following steps: face detection, image resizing, applying guided image filter on the resized image, extracting features, and recognizing faces with the help of the proposed CNN. Initially, the face region is extracted using the Viola-Jones algorithm and resized to 128x128. The entire methodology is depicted in Figure 1.

Figure 1. Block diagram of the proposed face recognition method

3.1. Guided image filter

To obtain information in images, the majority of applications in pattern recognition uses image filtering. The mean, Laplacian, Sobel, and Gaussian filters have been extensively utilized in image feature extraction, sharpening/blurring, restoration and edge detection. The bilateral filter is the most intuitive and simplest one among weighted average filters [33]. Even though the bilateral filter is successful in many circumstances, gradient reversal artifacts diminish its performance [34]-[36]. This problem is overcome by the guided filter. The guided filter is an explicit image filter obtained from a linear model and determines the filtering output based upon the content of the guidance image [37].

Let the I is a guidance image, and p is a filtering input image, the general linear translation-invariant filtering outcome at a pixel i is given as,

$$q_i = \sum_j W_{ij}(I)\, p_j \tag{1}$$

where i, and j are pixel indices, W_{ij} is the kernel.

The guided filter is a linear model between guidance I and the filtering output q and is given by:

$$q_i = a_k I_i + b_k, \forall i \in w_k \tag{2}$$

where (a_k, b_k) are linear coefficients in w_k.

To determine the coefficients (a_k, b_k), the output q is modeled as the input p subtracting few undesirable components n:

$$q_i = p_i - n_i \tag{3}$$

Minimize the following cost function in the window w_k to find the solution for the (2)

$$E(a_k, b_k) = \sum_{i \in w_k}((a_k I_i + b_k - p_i)^2 + \varepsilon\, a_k^2) \tag{4}$$

where ε is a regularization parameter. In (4) is the linear regressive model and its solution is given by,

$$a_k = \frac{\frac{1}{|w|}\sum_{i \in w_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \varepsilon} \tag{5}$$

$$b_k = \bar{p}_k - a_k \mu_k \tag{6}$$

Here μ_k and σ_k^2 are the mean and variance of I in w_k, $|w_k|$ is the total number of pixels in w_k and $\bar{p}_k = \frac{1}{|w|}\sum_{i \in w_k} p_i$ is the mean of p in w_k . After obtaining (a_k, b_k), we can find the filtering output q_i by (2). The input face image and the filtered output from the guided image filter are shown in Figure 2.


(a) (b) (c)

Figure 2. (a) Input face image (b) Face detection (c) Guided image filter output

3.2. Proposed convolutional neural network

In recent years convolutional neural networks have remarkably boosted the state-of-the-art performance for various visual tasks. For example, image retrieval, semantic segmentation, multitask learning, image classification, and person re-identification. Convolutional neural networks integrate both feature extraction and classification. The feature extraction is done by the convolutional layer and pooling layer. The fully connected layer is used for classification purposes.

The architecture of the proposed CNN is depicted in Figure 3. The proposed CNN consists of four convolutional layers with 8, 16, 32, and 64 filters. ReLU nonlinear activation function is utilized in each convolutional layer. In each convolutional layer, the stride is set to one. The input to the proposed CNN is a 128x128x1 image. The first convolutional layer consists of 5x5 kernels with eight filters. Hence the outcome of the conv1 is eight feature maps with size 124x124. Max pooling layers follow each convolutional layer with a 2x2 window and stride two. Maxpooling1 produces feature maps with a size of 62x62. In each max-pooling layer, the stride is set to two. The dimensions of the feature maps generated by conv2, conv3, and conv4 are 58x58x16, 25x25x32, and 9x9x64 respectively. Maxpooling2, maxpooling3, and maxpooling4 layers produce an output with dimensions 29x29x16, 13x13x32, and 4x4x64 respectively. The final max-pooling layer is followed by two fully connected layers with 1024 and 512 units. Finally, the softmax function is used for classification purposes. Stochastic Gradient Descent is utilized as an optimizer for training the data to the proposed CNN, with a base learning rate of 0.001. we used a batch size of four while training the network.

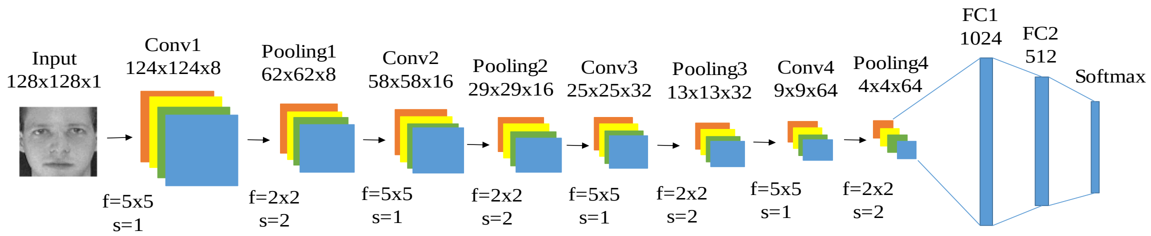


Figure 3. Architecture of the proposed CNN

3.3. The novelty of the proposed method

The novelty of the proposed methodology is removing the noise present in the face images before applying them to the proposed CNN and designing the CNN with a limited number of layers. Removing the noises existing in the face images improves the face recognition accuracy and designing the CNN with a fewer number of layers decreases the model complexity. Appending extra layers help to extract the more detailed features, but we can add layers up to a certain limit. After that, the model overfits the data which leads to errors like false positives. In addition to this, if we add more layers the number of weights in the network increases and leads to increase in the model complexity. To reduce this complexity, we designed the CNN with the optimum number of layers.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

We show the efficiency of our face recognition system across different poses, expressions, and illuminations using the ORL [38], JAFFE [39], and YALE [40] face datasets. We tested our method for a different radius (r) of the square window and regularization parameters (ε) of a guided image filter. We choose 70% of images in each class for training and the rest of the images were utilized for testing.

The ORL face database comprises 400 face images collected from 40 different persons with ten distinct images for each person. These images manifest variations in the pose, illumination, and facial expressions like smiling or not smiling, eyes closed or opened. The JAFFE face database is a collection of 213 grayscale images of ten Japanese female models. The database comprises facial expressions like the surprise, happiness, sadness, anger, fear, neutral, and disgust of each subject. The YALE face database includes 165 grayscale images of 15 subjects with 11 images per subject. Each subject contains images with the following configurations: center-light, happy, with glasses, sleepy, left-light, normal, sad, with no glasses, wink, right-light, and surprised. The images that belong to a single subject of these databases are shown in Figure 4.

Figure 5 shows the output images of the guided image filter for ORL, JAFFE, and YALE databases with different sets of parameters. For comparison purposes, we extracted the features from the second fully connected layer of the proposed CNN and classified them using a decision tree and random forest classifier. The efficiency of the classifier is evaluated using recognition rate (RR), area under curve (AUC), true positive rate (TPR), and false positive rate (FPR). The RR of the proposed method for the different radius (r) of the square window and regularization parameter (ε) is given in Table 1. The suggested method gives the best RR of 98.33%, 99.53%, and 98.65% on ORL, JAFFE, and YALE databases respectively for $r = 2$ and $\varepsilon = 0.4^2$. Compared to the random forest and decision tree classifiers softmax has given the best RR.

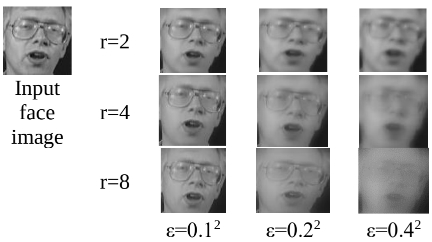
Table 2 gives the TPR for all the chosen face databases. The softmax classifier has given a maximum TPR of 98.57% whereas the decision tree and random forest classifiers have produced TPR of 99.61% and 98.65% on ORL, JAFFE, and YALE databases respectively for $r = 2$ and $\varepsilon = 0.4^2$. From Table 2, it is noticed that the softmax classifier has given high TPR compared to the decision tree and random forest. The FPR for the proposed method with different classifiers is given in Table 3. Low FPR is attained with a softmax classifier compared to the decision tree and random forest classifiers. The proposed method with softmax classifier has given an FPR of 0.02, 0.01, and 0.02 on ORL, JAFFE, and YALE databases for $r = 2$ and $\varepsilon = 0.4^2$. The AUC is determined and given in Table 4. The maximum value of the AUC with softmax classifier on ORL, JAFFE, and YALE databases is 99.52%, 99.78%, and 99.63%. From the values of Table 4, it is observed that the proposed method with the softmax classifier has more AUC than the other classifiers.

(a)

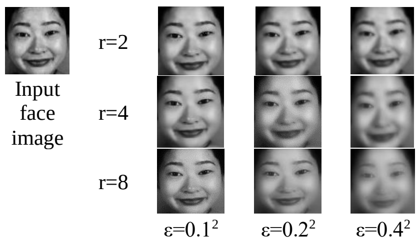
(b)

(c)

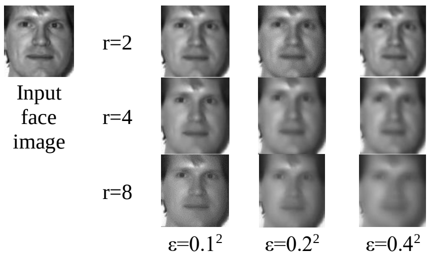
Figure 4. Images belong to a single subject of (a)ORL, (b)JAFFE and (c)YALE databases



(a)



(b)



(c)

Figure 5. The output images of a guided image filter for the gray-scale input from (a) ORL (b) JAFFE and (c) YALE database

Table 1. Recognition rate using decision tree, random forest, and softmax classifier

Radius (r)	Regularization parameter(ε)	ORL Decision Tree	ORL Random Forest	ORL Softmax	JAFFE Decision Tree	JAFFE Random Forest	JAFFE Softmax	YALE Decision Tree	YALE Random Forest	YALE Softmax
	0.1^2	95.25	95.87	96.67	94.28	95.52	98.33	95.17	95.28	97.78
2	0.2^2	94.36	94.64	95.83	93.46	96.31	98.33	95.45	96.43	97.78
	$\mathbf{0.4^2}$	**95.43**	**96.58**	**98.33**	**95.82**	**96.74**	**99.53**	**95.63**	**96.62**	**98.65**
	0.1^2	86.23	88.19	89.17	92.59	93.33	96.67	91.24	93.48	97.89
4	0.2^2	87.62	89.45	91.67	91.35	94.63	96.67	92.87	94.24	97.78
	0.4^2	88.48	90.24	91.67	89.75	92.44	95.00	89.59	92.31	95.56
	0.1^2	86.41	87.52	90.83	88.93	89.93	93.33	90.88	93.97	97.78
8	0.2^2	86.67	87.86	90.83	89.82	92.12	93.33	91.73	94.66	97.78
	0.4^2	85.41	88.38	90.00	90.91	91.53	93.33	87.24	89.15	93.33

Table 2. True positive rate using decision tree, random forest, and softmax classifier

Radius (r)	Regularization parameter(ε)	ORL Decision Tree	ORL Random Forest	ORL Softmax	JAFFE Decision Tree	JAFFE Random Forest	JAFFE Softmax	YALE Decision Tree	YALE Random Forest	YALE Softmax
	0.1^2	95.25	95.87	96.67	94.28	95.52	98.33	95.17	95.28	97.78
2	0.2^2	94.56	94.64	95.83	93.46	96.52	98.33	95.45	96.43	97.78
	0.4^2	95.43	96.88	98.57	95.82	96.94	99.61	95.63	96.93	98.65
	0.1^2	86.23	88.19	90.24	93.25	93.33	96.67	91.24	93.48	98.21
4	0.2^2	87.62	89.45	91.67	91.35	94.63	96.67	93.52	95.26	97.78
	0.4^2	88.48	90.24	91.67	90.57	93.64	95.42	90.25	93.43	96.25
	0.1^2	86.41	88.22	90.83	88.93	89.93	94.36	91.68	94.72	97.78
8	0.2^2	86.92	87.86	90.83	89.82	92.12	94.36	92.13	94.89	97.78
	0.4^2	85.41	88.38	91.62	90.91	91.53	94.36	87.24	89.15	94.73

Table 3. False positive rate using decision tree, random forest, and softmax classifier

Radius (r)	Regularization parameter(ε)	ORL Decision Tree	ORL Random Forest	ORL Softmax	JAFFE Decision Tree	JAFFE Random Forest	JAFFE Softmax	YALE Decision Tree	YALE Random Forest	YALE Softmax
	0.1^2	0.06	0.04	0.03	0.06	0.05	0.02	0.07	0.04	0.03
2	0.2^2	0.08	0.07	0.05	0.07	0.05	0.02	0.08	0.06	0.03
	0.4^2	0.06	0.03	0.02	0.06	0.04	0.01	0.07	0.04	0.02
	0.1^2	0.09	0.08	0.07	0.09	0.08	0.04	0.08	0.05	0.03
4	0.2^2	0.05	0.04	0.06	0.09	0.07	0.04	0.07	0.06	0.03
	0.4^2	0.09	0.08	0.06	0.08	0.07	0.05	0.09	0.08	0.04
	0.1^2	0.09	0.09	0.07	0.08	0.06	0.05	0.08	0.07	0.03
8	0.2^2	0.09	0.09	0.07	0.08	0.07	0.05	0.07	0.06	0.03
	0.4^2	0.09	0.08	0.06	0.07	0.04	0.05	0.08	0.07	0.05

Table 4. Area under curve using decision tree, random forest, and softmax classifier

Radius (r)	Regularization parameter(ε)	ORL Decision Tree	ORL Random Forest	ORL softmax	JAFFE Decision Tree	JAFFE Random Forest	JAFFE softmax	YALE Decision Tree	YALE Random Forest	YALE softmax
	0.1^2	96.53	97.84	98.73	95.94	96.45	99.53	96.67	97.59	99.24
2	0.2^2	95.41	95.21	97.81	95.63	97.28	99.53	96.53	97.28	99.24
	0.4^2	96.82	97.23	99.52	97.95	98.92	99.78	96.92	97.63	99.63
	0.1^2	87.42	88.44	93.72	93.48	95.47	98.75	93.67	96.98	98.76
4	0.2^2	88.85	90.28	95.38	94.78	95.58	98.75	94.27	98.83	99.24
	0.4^2	89.55	91.68	95.38	92.46	94.64	98.43	94.44	96.16	98.63
	0.1^2	87.29	88.73	94.68	93.37	96.34	98.47	92.37	94.31	99.21
8	0.2^2	87.76	88.43	94.68	92.28	95.76	98.47	93.66	97.44	99.21
	0.4^2	86.45	89.92	93.72	94.19	96.29	98.47	91.34	95.52	98.78

The ROC curves for the proposed technique with softmax classifiers are depicted in Figure 6. The performance comparison of the suggested method with some of the existing methods is encapsulated in Table 5. From the values of Table 5, it is noticed that the proposed face recognition approach gives a good recognition rate than some of the earlier approaches.

Image data augmentation enlarges the size of the training dataset by producing the modified versions of the images in the dataset. Data augmentation can improve the performance of the proposed face recognition system. We carried out horizontal and vertical flipping, rotation by 45 degrees, and zooming for generating additional images. The recognition rate of the proposed method with and without the data augmentation is given in Table 6.

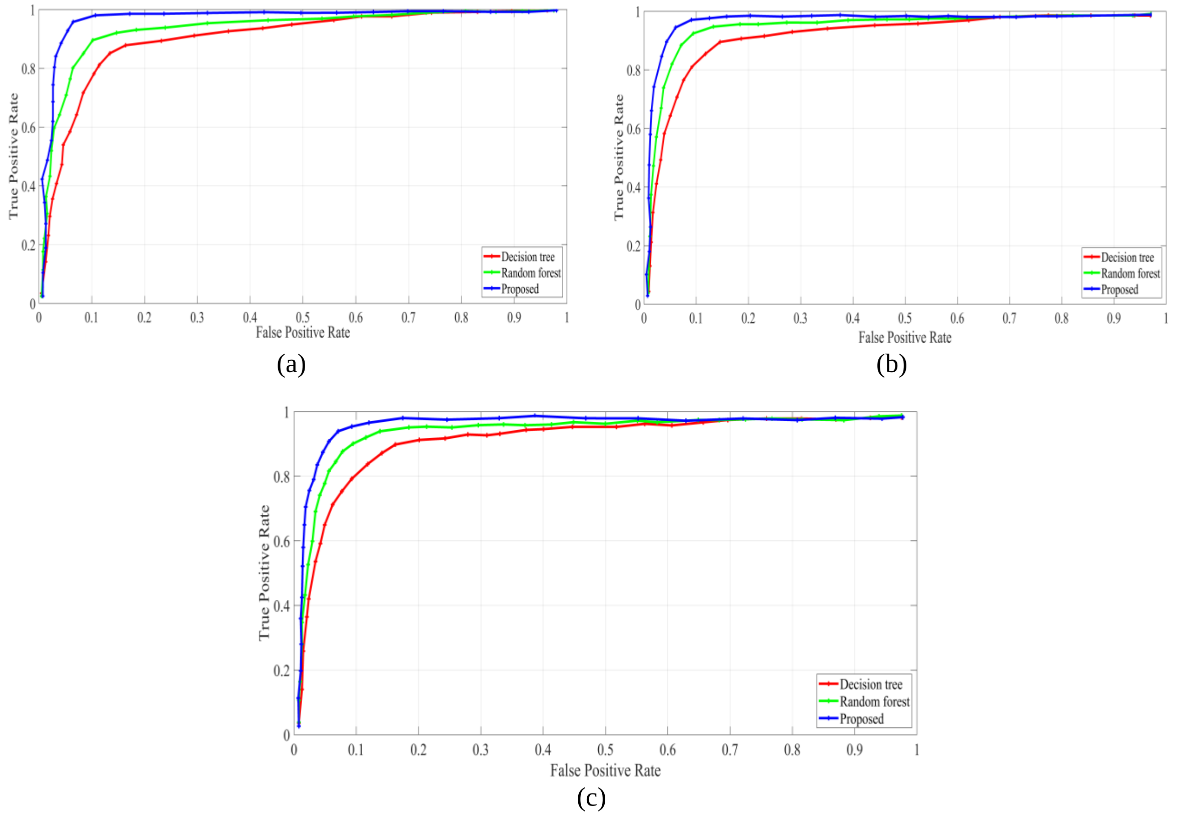


Figure 6. ROC curves for (a) ORL (b) JAFFE and (c) YALE databases for $r = 2$ and $\varepsilon = 0.4^2$

Table 5. Comparison of recognition rate (%) with some of the existing techniques

Method	Database		
	ORL	JAFFE	YALE
CLDA [5]	94.06		
PCA [8]	89.50		
FLD [8]	91.00		
PCA image reconstruction + LDA [14]	97.20		
GFDBN [20]	94.98		
DIWTLBP [22]	97.00		
DSDSA [24]	98.00		
Proposed	**98.33**		
FLLEPCA [10]		94.98	
Single 2D NNRW [15]		97.00	
PSO [17]		98.80	
Proposed		**99.53**	
OPR [18]			94.15
PLR [19]			96.23
RDCDL [23]			97.22
DSDSA [24]			98.16
Proposed			**98.65**

Table 6. Recognition rate of the proposed method with and without data augmentation

	Database		
	ORL	JAFFE	YALE
Without Data Augmentation	98.33%	99.53%	98.65%
With Data Augmentation	99.17%	99.74%	99.32%

5. CONCLUSION

In this work, a face recognition approach using a guided image filter and a convolutional neural network was proposed. First, the face region of the test image is extracted using the Viola-Jones algorithm and then resized. The resized image was passed through a guided image filter. A guided image filter smoothens the face image, then the proposed CNN was utilized to extract the features and classify the input face image. Here, the softmax classifier, which gives good results than the decision tree and random forest, was used in CNN's classifier section. The capability of the proposed approach was compared with some of the earlier methods. From the comparative results, it is found that the suggested technique produces better results than some of the existing methods. Based on the experimental results, it is concluded that our proposed method can be used for face recognition.

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BIOGRAPHIES OF AUTHORS

Yallamandaiah S received his B. Tech degree from JNTUH, Hyderabad, and M. Tech degree from JNTUK, Kakinada. Currently, he is a Research Scholar at the SENSE, VIT-AP University, India. His research fields include Image Processing and Machine Learning.

Purnachand N received his M.Tech degree from VIT University, Vellore, India, and PhD degree from University of Aveiro, Aveiro Portugal. Currently, he is working as Associate Professor at VIT-AP University, India. His fields of research contain Image Processing, Video Processing, and Pattern Recognition.